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Artificial Intelligent in Automotive Suspension System for Vertical Body Vibration Improvement using Neural Network

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Abstract

Introduction/Main Objectives: Vehicle suspension systems are essential for maintaining ride comfort and stability. Conventional passive systems often fail to adapt to varying road conditions, leading to compromises in performance. Artificial Intelligence (AI), particularly Neural Networks (NN), offers a promising solution for modelling nonlinear dynamics and enabling adaptive control in suspension systems. The main objectives are to apply AI techniques using Neural Networks for optimizing suspension performance, to model and analyze a two-degree-of-freedom (2DOF) vertical body vibration system based on a quarter-car model and to improve ride comfort and stability by minimizing body acceleration and tire load variations.

Background Problems: Traditional suspension systems lack adaptability and struggle to balance comfort with handling. Road irregularities introduce nonlinear vibrations that passive systems cannot effectively mitigate. This creates a need for intelligent, real-time control strategies.

Research Methods: A two-degree-of-freedom (2DOF) quarter-car model was developed to represent the dynamic interaction between the sprung and unsprung masses. Simulation data were generated under various road excitation conditions to capture the system's response to real-world disturbances. A feedforward neural network was then trained using this data to predict optimal suspension responses, enabling adaptive control strategies. Finally, the performance of the AI-based suspension system was compared with that of a conventional passive suspension system to evaluate improvements in ride comfort and stability.

Finding/Results: The neural network successfully learned complex nonlinear relationships within suspension dynamics. AI-based control strategies demonstrated superior performance in reducing body acceleration and maintaining tire contact compared to passive systems, resulting in improved ride quality.

Conclusion: AI-driven suspension systems using Neural Networks provide an effective framework for real-time vibration control. This approach enhances comfort and stability, paving the way for next-generation intelligent vehicles.

Keywords: Artificial intelligence (AI), neural networks (NN), automotive suspension system, vertical body vibration, vibration reduction.

Introduction

Vehicle vertical dynamics refers to the study of motion and forces acting on a vehicle in the vertical direction, primarily influenced by road irregularities, suspension characteristics, and tire compliance. This domain is critical for ensuring ride comfort, handling stability, and passenger safety. When a vehicle traverses uneven surfaces, disturbances such as bumps and potholes generate vertical excitations that propagate through the suspension system to the chassis and passenger compartment. These excitations lead to vibrations, which, if not properly controlled, can degrade ride quality, increase driver fatigue, and accelerate component wear (Garcia-Pozuelo et al., 2014). The suspension system plays a vital role in mitigating these vibrations by absorbing and dissipating energy, maintaining tire contact with the road, and isolating the vehicle body from harsh impacts. However, suspension dynamics are complex and exhibit nonlinear behaviors due to varying loads, damping characteristics, and road conditions (Ka'ka et al., 2023). Traditional suspension systems often rely on passive components such as springs and dampers, which provide limited adaptability to changing conditions. Consequently, modern research emphasizes semi-active and active suspension systems that can adjust damping forces in real time to improve comfort and stability (Du, Li, & Ning, 2024).

Vertical dynamics modeling is commonly approached using simplified representations such as the quarter-car model, which captures the essential behavior of the sprung and unsprung masses connected by suspension elements (Chitale, Patil, & Pathan, 2023). This model helps analyze parameters like suspension stiffness, damping, and tire compliance, which significantly influence vertical acceleration and vibration transmission. Studies have shown that optimizing these parameters can reduce vertical acceleration, thereby enhancing ride comfort and safety (Bezabh et al., 2023). Road irregularities, including speed bumps and potholes, introduce additional challenges to vertical dynamics. Improperly designed road features can cause excessive vibrations, loss of tire grip, and even structural damage to vehicles (Garcia-Pozuelo et al., 2014). Therefore, understanding the interaction between road geometry, vehicle speed, and suspension characteristics is essential for both vehicle design and infrastructure planning. Recent advancements in control strategies, such as fuzzy logic, neural networks, and sliding mode control, have been applied to suspension systems to address nonlinearities and uncertainties inherent in vertical dynamics (Du et al., 2024). These approaches aim to achieve an optimal balance between ride comfort and road holding, which is particularly important for autonomous and electric vehicles where noise vibration harshness (NVH) performance is a key design criterion (Deubel, Schneider, & Prokop, 2025).

Active suspension systems controlled by algorithms such as Proportional-Integral-Derivative (PID) regulate suspension actuators to minimize body displacement and acceleration, improving vibration isolation and road holding. However, traditional PID controllers assume linearity and fixed gains, which limits adaptability under varying loads and road conditions (Emam, 2015). Recent studies have demonstrated that PID-based active suspension systems can reduce body acceleration by over 90% compared to passive systems, significantly enhancing ride quality (Parvez, Chauhan, & Srivastava, 2024). Modified PID structures and hybrid approaches, such as PID combined with Sliding Mode Control (PID-SMC), further improve performance by addressing nonlinearities and uncertainties in suspension dynamics (Nguyen, 2023). These advancements enable real-time vibration control, ensuring stability and comfort even under random road excitations. Despite limitations in adaptability, PID remains a widely used baseline due to its simplicity and effectiveness, often serving as a foundation for advanced adaptive and intelligent control strategies. This conventional PID controller have several limitations when applied to vehicle suspension systems. Firstly, it operates under the assumption of system linearity, whereas suspension dynamics are inherently nonlinear due to factors such as road irregularities, load variations, and tire behavior. Secondly, PID controllers rely on fixed proportional, integral, and derivative gains, which are typically tuned for a specific operating condition. This becomes problematic because suspension systems encounter diverse scenarios involving varying loads, speeds, and terrains. Lastly, PID controllers exhibit poor adaptability, making them ineffective in responding to real-time changes such as sudden bumps or dynamic weight shifts, which are common in practical driving environments.

Neural Network (NN)-based control strategies have emerged as a promising solution to overcome these limitations by leveraging their ability to approximate nonlinear functions and adapt to dynamic environments. NN controllers can learn complex relationships between suspension parameters and vehicle responses, enabling real-time optimization of damping and stiffness. Studies have shown that NN-based active suspension systems outperform PID-controlled systems in reducing body acceleration, suspension deflection, and tire load under random road excitations (Kalaivani, Sudhagar, & Lakshmi, 2016). Adaptive NN controllers, such as radial basis function networks and multilayer perceptron's, have been successfully applied to estimate unknown dynamics and compensate for uncertainties, ensuring robust performance even under actuator saturation and parameter variations (Zhao et al., 2016; Ghahremani et al., 2018). Recent advancements integrate NN with hybrid approaches like sliding mode control and reinforcement learning, achieving superior vibration suppression and improved ride comfort without compromising road holding (Dridi, Hamza, & Ben Yahia, 2023). Furthermore, digital twin technology combined with NN enables predictive and adaptive suspension control, enhancing comfort by up to 8.46% compared to PID methods (Qiu et al., 2025). These developments highlight NN's potential for intelligent suspension systems, offering adaptability, robustness, and improved performance in complex, nonlinear vehicle dynamics.

This paper investigates a two-degree-of-freedom (2DOF) vertical body dynamics model to analyze vehicle vibration behaviours under road disturbances. An active suspension system is employed to enhance ride comfort and stability compared to conventional passive suspensions. Initially, a PID controller is implemented to regulate suspension actuator forces, reducing body displacement and acceleration. Artificial intelligent (AI) approach using neural network (NN) strategy is introduced that learns from the PID controller's behaviour and progressively improves performance through adaptive learning. The NN controller approximates the nonlinear dynamics of the suspension system and adjusts control actions in real time, ensuring better vibration suppression under diverse road profiles. Simulation results demonstrate that the NN-based controller significantly reduces vertical acceleration and suspension deflection compared to PID, achieving superior ride comfort and road holding. This hybrid approach leverages the simplicity of PID for initial tuning and the adaptability of NN for continuous optimization, making it a promising solution for intelligent suspension systems.

Research Methods

The quarter car two-degree-of-freedom (2DOF) vertical body dynamics model represents the sprung mass, m_b (vehicle body) and unsprung mass (wheel assembly) connected through suspension and tire elements (Figure 1). This simplified model is widely used for analyzing ride comfort and suspension performance. The derivation of the 2DOF vertical body dynamics model is based on several simplifying assumptions to ensure analytical tractability and focus on ride comfort analysis. First, the suspension system is assumed to exhibit linear spring and damper characteristics, meaning the stiffness and damping forces vary proportionally with displacement and velocity, respectively. Second, the model considers only small vertical displacements, which is a valid approximation for comfort analysis under normal driving conditions where suspension travel remains within its operational range. Finally, lateral and longitudinal dynamics are neglected, allowing the study to concentrate exclusively on vertical motion and vibration behavior without the complexity introduced by steering or acceleration effects. The modeling of the 2DOF vertical body dynamics is implemented in MATLAB/Simulink to simulate vehicle suspension behavior under various road excitations. The system consists of two masses: the sprung mass representing the vehicle body and the unsprung mass representing the wheel assembly. These masses are connected through suspension elements characterized by stiffness and damping, while the tire stiffness links the unsprung mass to the road surface. The governing differential equations derived from Newton's second law are formulated for both masses, incorporating suspension forces, damping forces, and active control input. These equations are then converted into a state-space representation and implemented in Simulink using blocks for integrators, gains, and summation points. Road disturbances such as step, sine, and random profiles are applied as input signals to the road displacement block. The active suspension force is modeled as an external input, allowing integration of different control strategies such as PID and neural network controllers. Simulation outputs include body displacement, body acceleration, suspension deflection, and tire load, which are analyzed to evaluate ride comfort and stability. The model is validated by comparing passive and active suspension responses under identical road conditions. The derivations of the equations of motions using forces,

$$F_{mb} = m_b \ddot{z}_b \tag{1}$$

$$F_{cs} = c_s(\dot{z}_w - \dot{z}_b) \tag{2}$$

$$F_{ks} = k_s(z_w - z_b) \tag{3}$$

$$F_{mt} = m_t \ddot{z}_w \tag{4}$$

$$F_{kt} = k_t(z_r - z_w) \tag{5}$$

Where,

F_{mb} = force due to mass of vehicle body

F_{cs} = force of the suspension damping

F_{ks} = force of the suspension stiffness

F_{mt} = force due to the mass of the wheel

m_b = mass of the vehicle body

c_s = suspension damping coefficient

k_s = suspension spring stiffness

z_b = vertical displacement of the vehicle body

m_t = mass of the wheel

k_t = tire stiffness

z_w = vertical displacement of the wheel

z_r = road irregularities

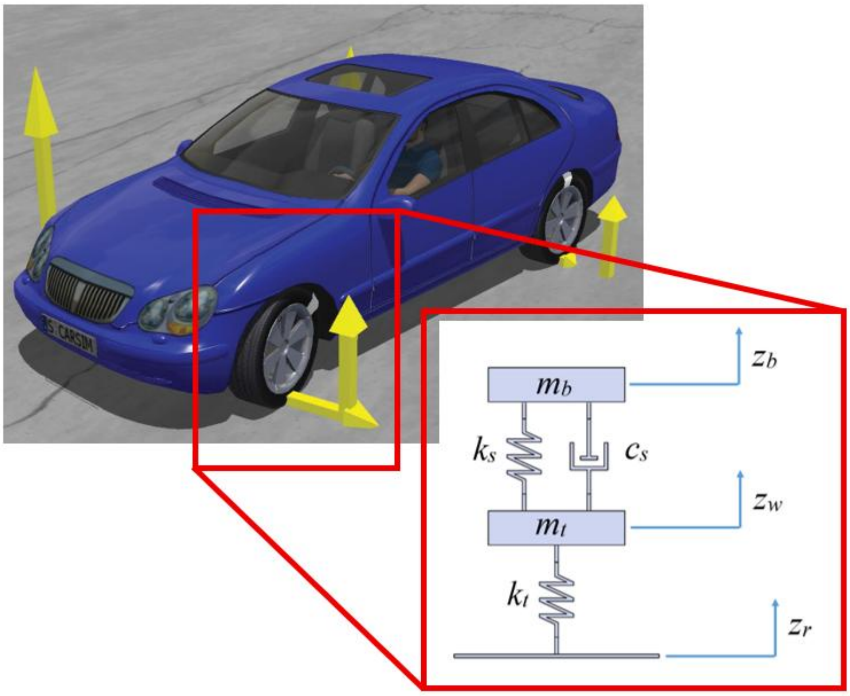

Figure 1. Quarter car vertical dynamic 2DOF model
Source: Author's Work, 2025.

Using Newton's 2nd Law,

$$F_{mb} = F_{cs} + F_{ks} \tag{6}$$

$$m_b\ddot{z}_b = F_{cs} + F_{ks} \tag{7}$$

$$\ddot{z}_b = \frac{1}{m_b}(F_{cs} + F_{ks}) \tag{8}$$

$$m_b\ddot{z}_b = c_s(\dot{z}_w - \dot{z}_b) + k_s(z_w - z_b) \tag{9}$$

$$F_{mt} = -F_{cs} - F_{ks} + F_{kr} \tag{10}$$

$$m_t\ddot{z}_w = -F_{cs} - F_{ks} + F_{kr} \tag{11}$$

$$\ddot{z}_w = \frac{1}{m_t}(-F_{cs} - F_{ks} + F_{kr}) \tag{12}$$

$$m_t\ddot{z}_w = -c_s(\dot{z}_w - \dot{z}_b) - k_s(z_w - z_b) + k_t(z_r - z_w) \tag{13}$$

Table 1. Vehicle parameters

	Parameter	Value
1.	m_b	454.5 kg
2.	c_s	2400 Ns/m
3.	k_s	22000 N/m
4.	m_t	45.45 kg
5.	k_t	17600 N/m

The Simulink models for Eqn. (2), (3) and (9) are,

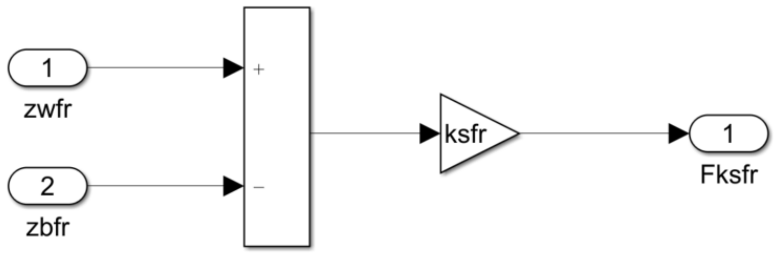

Figure 2. Simulink model for F_{ks}
Source: Author'S work, 2025.

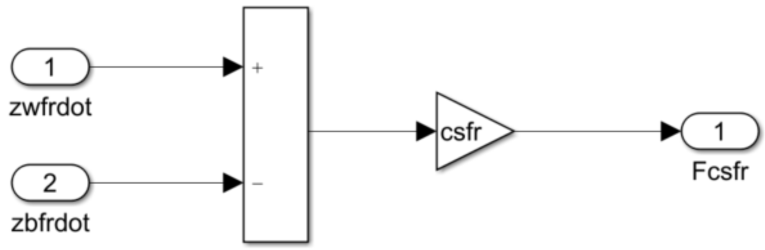

Figure 3. Simulink model for F_{cs}
Source: Author'S work, 2025.

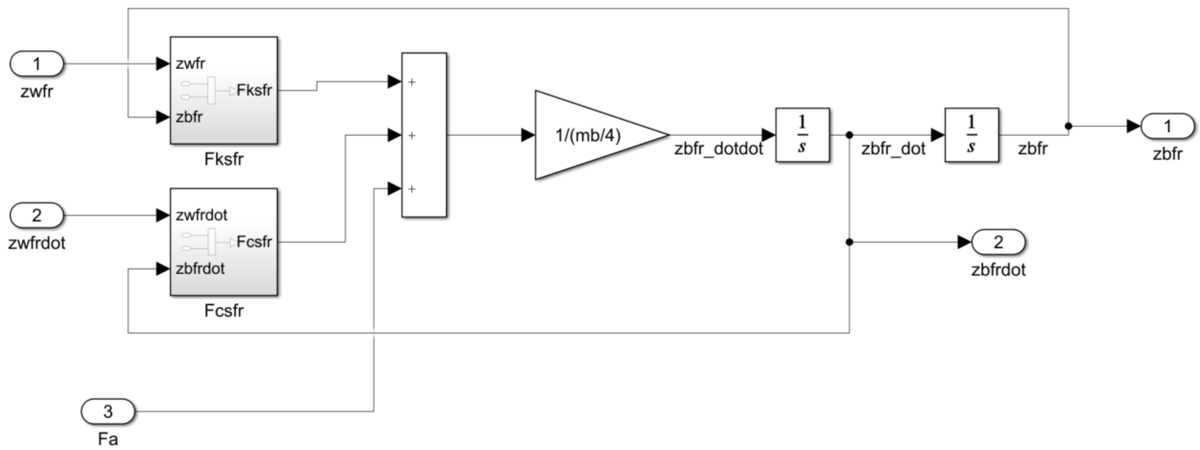

Figure 4. Simulink model for vehicle body vertical displacement
Source: Author'S work, 2025.

The Simulink models for Eqn. (5) and (13) are,

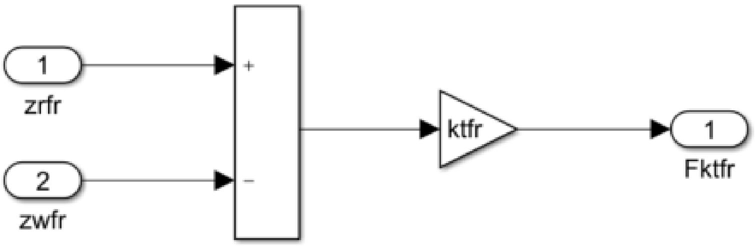

Figure 5. Simulink model for F_{kt}
Source: Author'S work, 2025.

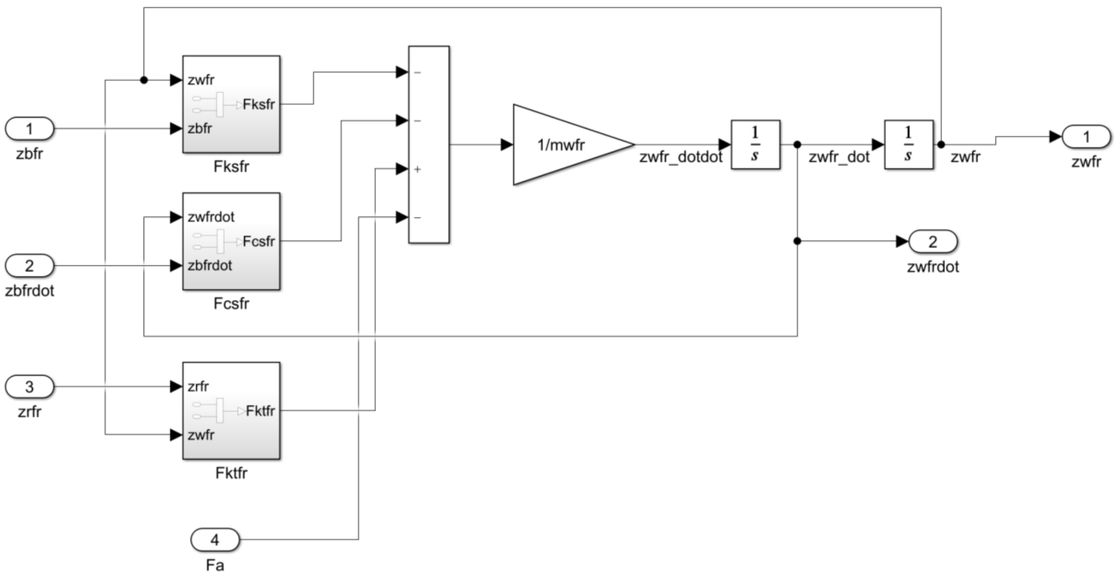

Figure 6. Simulink model for wheel vertical displacement
Source: Author'S work, 2025.

Combining the models with the introduction of active suspension force, F_a,

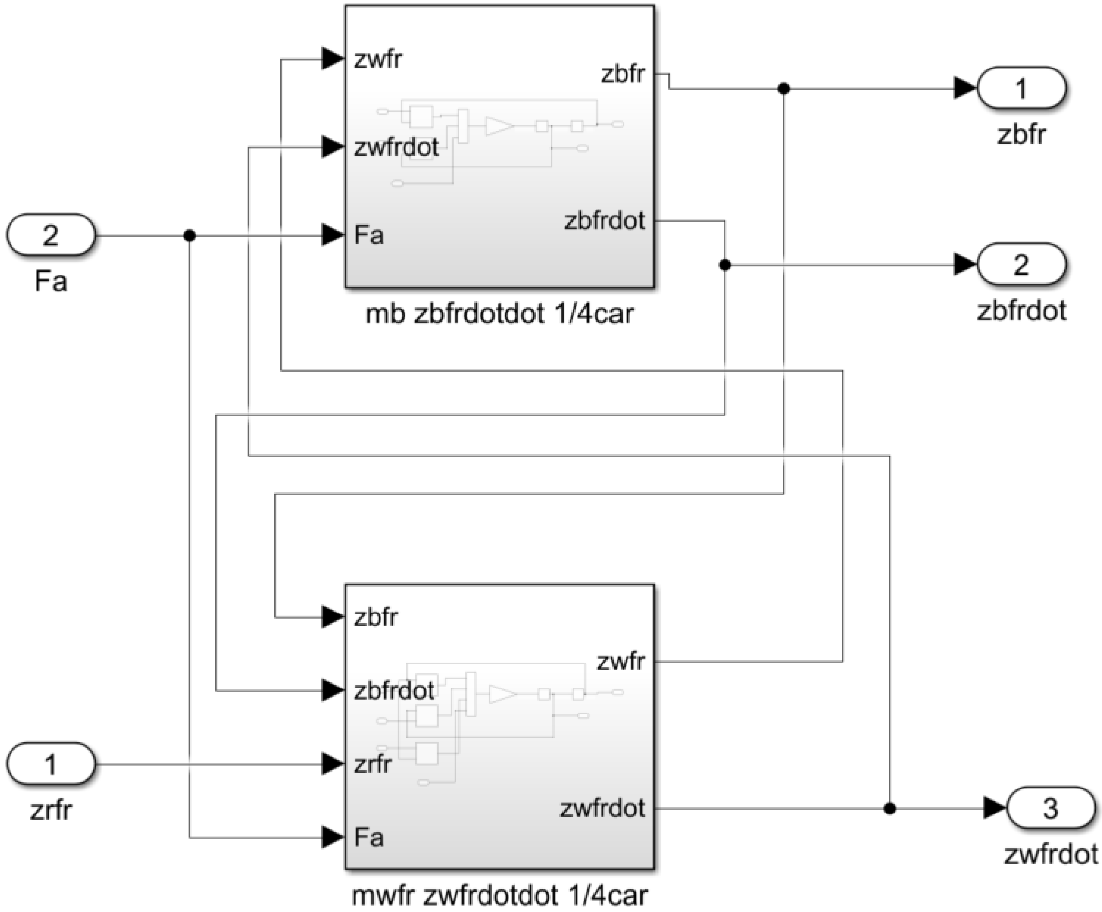

Figure 7. 2DOF model
Source: Author’S work, 2025.

Further simplify the model into subsystem,

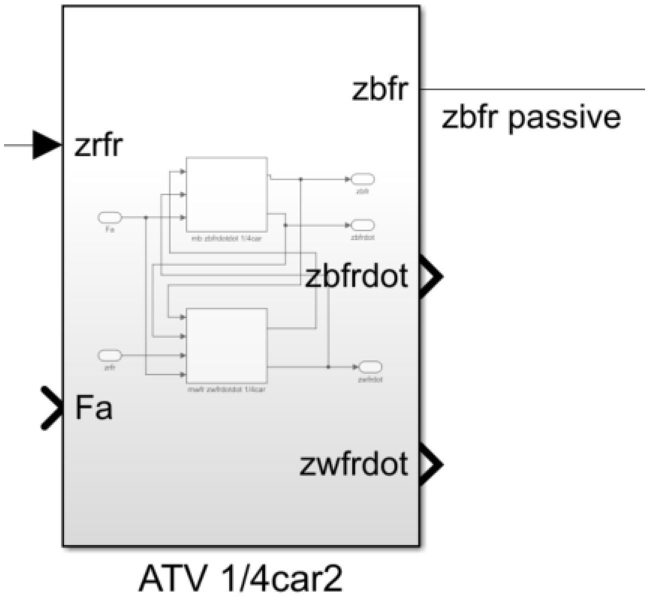

Figure 8. 2DOF model with subsystem
Source: Author'S work, 2025.

To evaluate the performance of the 2DOF vertical body dynamics model and its control strategies, three types of road input excitations are considered: step, sine, and random road profiles. The step input (Figure 9) simulates a sudden change in road elevation, such as encountering a speed bump or curb (0.05 m), and is used to assess the suspension's transient response and stability. The sine input (Figure 10) represents periodic road undulations, enabling analysis of the system's frequency response and resonance characteristics under harmonic excitation (0.05 m at frequency π rad/s). Finally, the random input (Figure 11) models real-world road irregularities based on ISO road roughness standards (-0.05 to 0.05 m), providing a realistic scenario for evaluating ride comfort and vibration suppression. These inputs are applied to the road displacement term $z_r(t)$in the unsprung mass equation, and simulations are performed using MATLAB/Simulink.

The application of a PID controller in an active suspension system aims to improve ride comfort and stability by minimizing body displacement and acceleration. The PID controller (Figure 12) is designed based on the 2DOF vertical body dynamics model, where the control input is the active suspension force applied between the sprung and unsprung masses. The methodology begins with defining the control objective, which is to maintain the vehicle body position close to a reference level while reducing vibrations caused by road disturbances. The error signal is computed as the difference between the desired body displacement and the actual displacement. The PID controller generates the control force using three components: proportional action to reduce instantaneous error, integral action to eliminate steady-state error, and derivative action to anticipate future error trends. Tuning of PID gains (K_p, K_i, K_d) is performed using methods such as Ziegler–Nichols or optimization algorithms to achieve a balance between ride comfort and road holding. The controller is implemented in MATLAB/Simulink, where the active suspension force block receives the PID output. Simulations are conducted under step, sine, and random road inputs to evaluate system performance in terms of body acceleration, suspension deflection, and tire load. Comparative analysis with passive suspension highlights the effectiveness of PID control in vibration suppression.

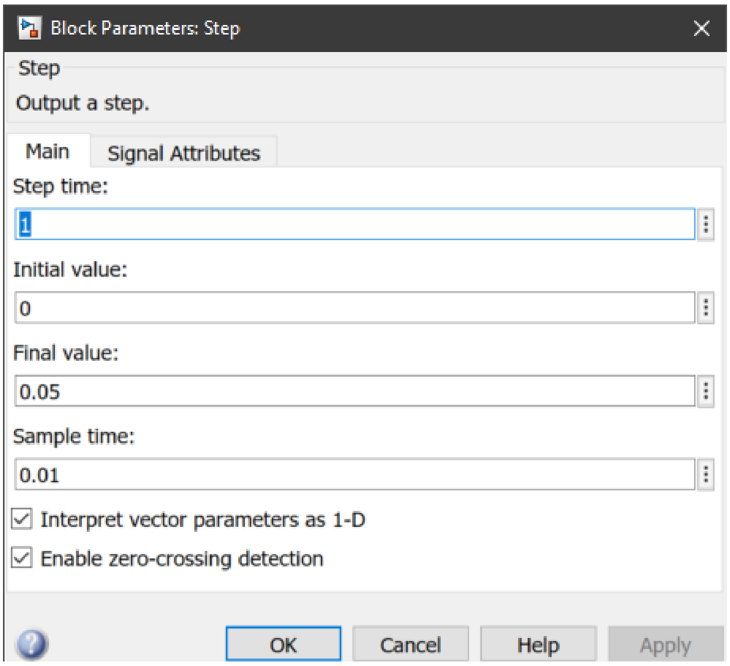

Figure 9. Step input parameters
Source: Author'S work, 2025.

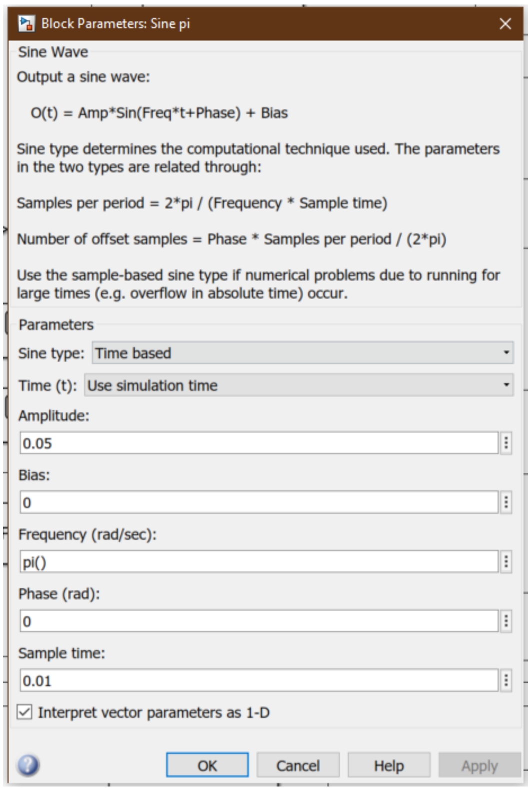

Figure 10. Sine input parameters
Source: Author'S work, 2025.

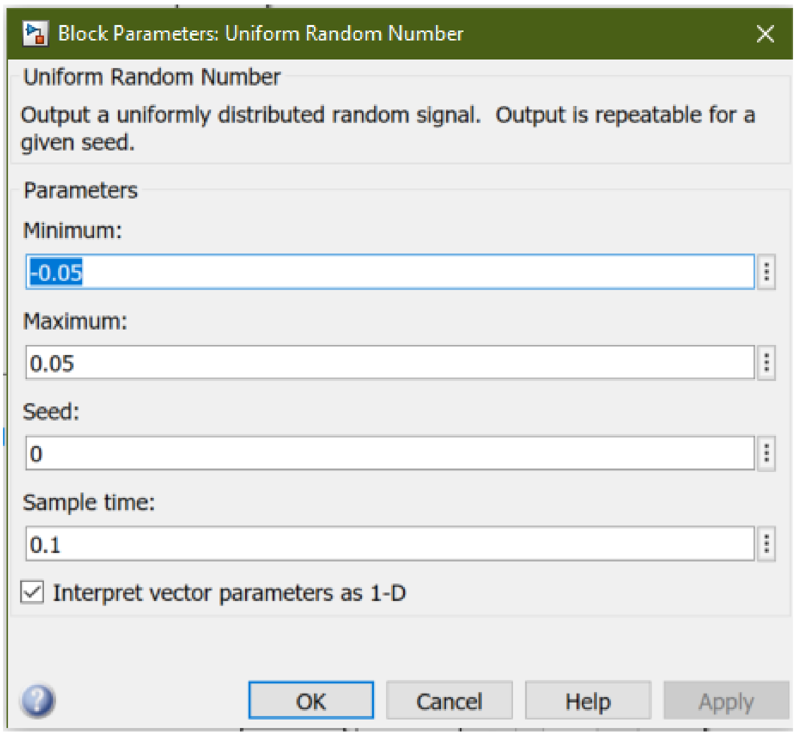

Figure 11. Random input parameters.
Source: Author'S work, 2025.

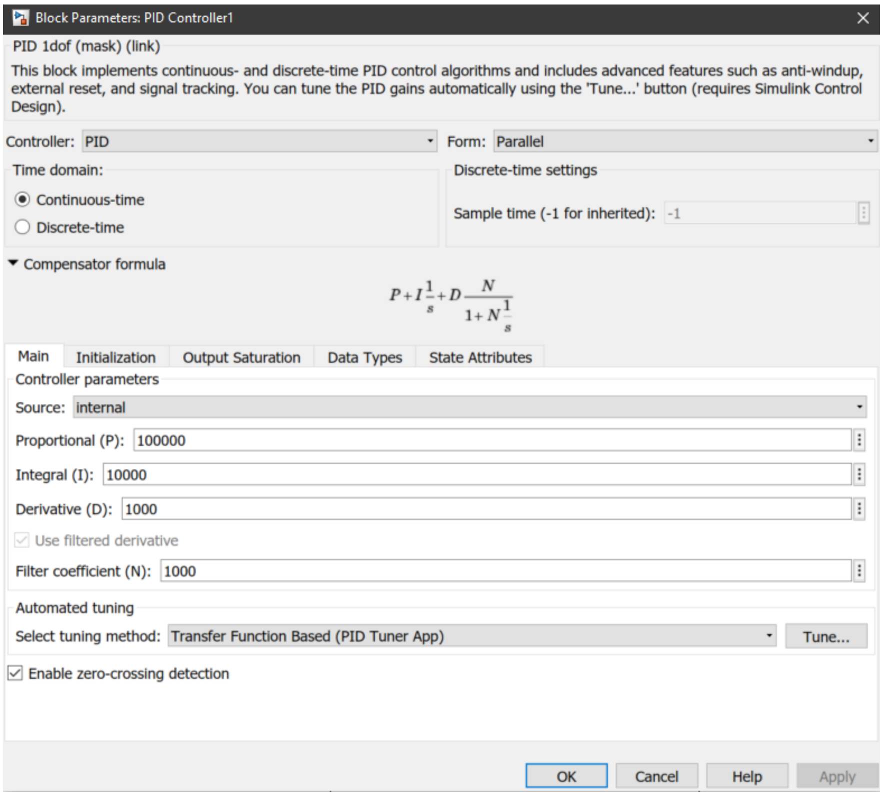

Figure 12. PID parameters
Source: Author'S work, 2025.

A Neural Network (NN) controller is introduced to the active suspension system to enhance vibration suppression by learning (Figure 13) from the optimal performance of a tuned PID controller. Initially, the 2DOF vertical body dynamics model is implemented in MATLAB/Simulink, and a PID controller is designed and tuned using optimization techniques such as Ziegler–Nichols or Particle Swarm Optimization to achieve the best trade-off between ride comfort and road holding. The system is simulated under various road excitations (step, sine, and random profiles), and performance metrics such as body acceleration, suspension deflection, and tire load are recorded. These optimal PID responses serve as training data for the NN, which is structured as a feedforward network with backpropagation learning. The NN learns the nonlinear mapping between road input, system states, and optimal control force generated by the PID controller. Once trained, the NN replaces the PID controller in the active suspension system, providing adaptive control that can handle nonlinearities and varying operating conditions. The NN-based controller is validated through simulations under the same road profiles, and its performance is compared against both passive and PID-controlled suspensions. Key evaluation criteria include vibration reduction, adaptability, and computational efficiency.

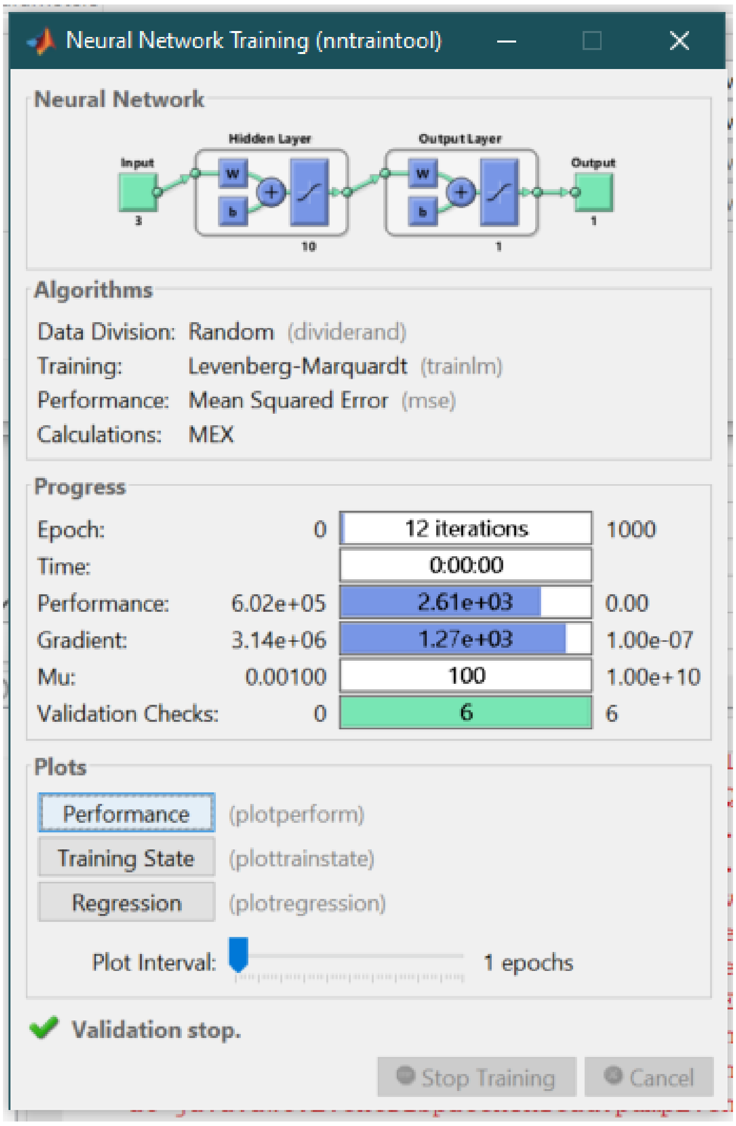

Figure 13. NN training
Source: Author'S work, 2025.

The comparative analysis is conducted using a 2DOF vertical body dynamics model implemented in MATLAB/Simulink. Three suspension configurations are modeled: Passive suspension, consisting of fixed spring and damper elements; Active suspension with PID control, where an optimized PID controller generates the active force to minimize body displacement and acceleration; and Active suspension with Neural Network (NN) control, which learns from the optimal performance data of the PID controller and adapts to nonlinear dynamics. Each configuration is subjected to identical road excitations, including step input (to evaluate transient response), sine input (to analyze frequency response), and random input (to simulate real-world road irregularities). Performance metrics include body acceleration, suspension deflection, and tire load, which are recorded and compared across all configurations. MATLAB/Simulink scopes and data logging are used to capture time-domain responses, while frequency-domain analysis is performed for sinusoidal inputs. Statistical measures such as RMS acceleration and peak displacement are computed to quantify ride comfort and stability. The results are presented in comparative plots and tables, highlighting improvements achieved by active suspension systems over passive suspension, and demonstrating the superior adaptability and vibration suppression capability of NN-based control compared to PID.

Results

The NN training results are shown in Figures 14 and 15. The Neural Network (NN) training for active suspension control achieved its best validation performance at epoch 6, where the Mean Squared Error (MSE) reached its minimum value, indicating optimal learning and generalization. This early convergence demonstrates that the NN effectively captured the nonlinear dynamics of the suspension system using the training data derived from the PID controller's optimal performance. Additionally, the regression analysis between the predicted outputs and the target values yielded a correlation coefficient (R) of 0.99885, which is very close to 1. This high R-value confirms an excellent fit between the NN predictions and the desired control force, signifying that the network accurately learned the underlying relationship and can reliably reproduce optimal control actions. These results validate the robustness and accuracy of the NN-based controller, making it suitable for real-time implementation in active suspension systems to improve ride comfort and vibration suppression.

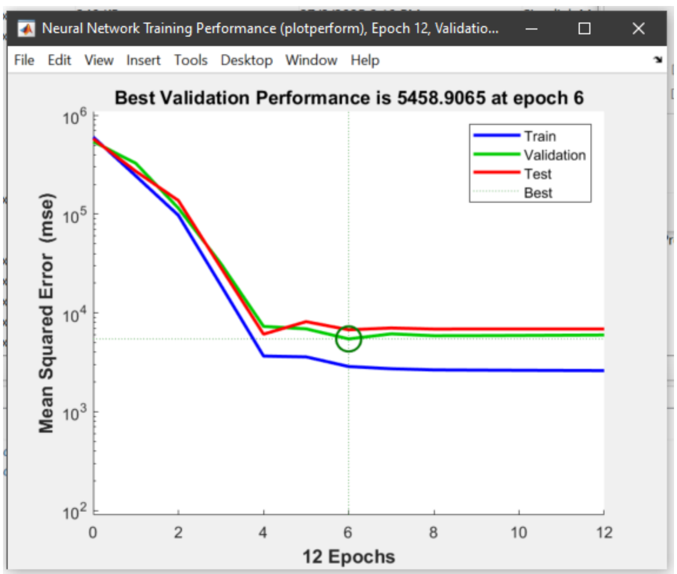

Figure 14. NN training performance
Source: Author'S work, 2025.

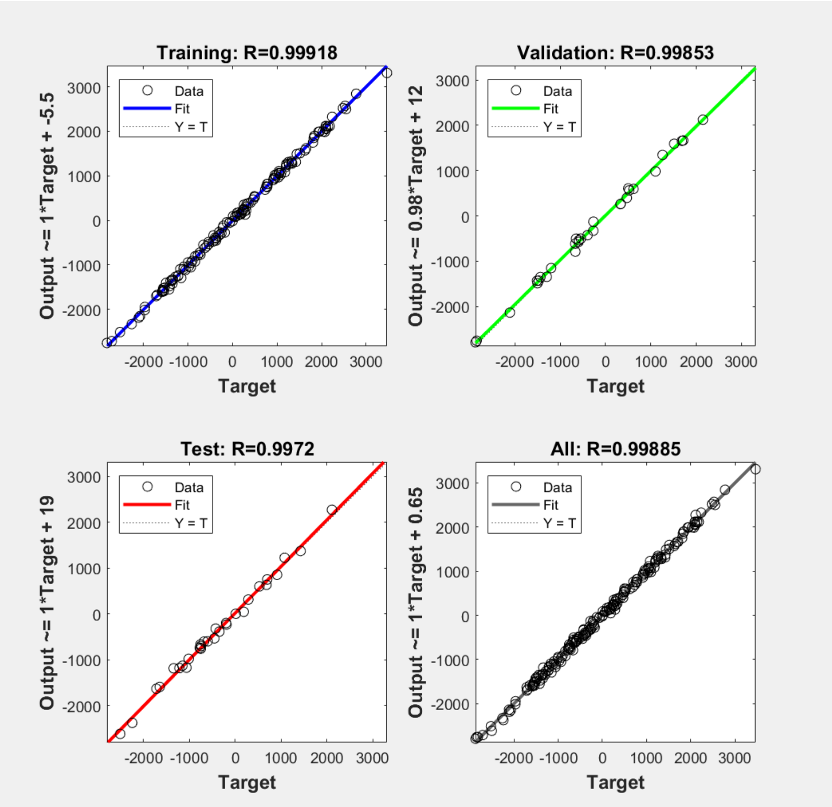

Figure 15. NN training regression
Source: Author'S work, 2025.

The simulation results under a step road input demonstrate that the Neural Network (NN)-controlled active suspension significantly outperforms both passive suspension and PID-controlled active suspension in reducing vertical body vibration (Figure 16). For the passive system, the body displacement exhibited large oscillations following the step disturbance, while the PID controller reduced these oscillations but still showed noticeable fluctuations. In contrast, the NN-based controller achieved superior damping performance, maintaining body displacement fluctuations at less than 0.03 m throughout the transient response. This improvement indicates that the NN effectively learned and optimized control actions beyond the limitations of PID, providing faster settling time and minimal overshoot. The enhanced vibration suppression translates into improved ride comfort and stability, validating the effectiveness of AI-based control strategies for active suspension systems.

Under a sine road excitation, the Neural Network (NN)-controlled active suspension closely imitates the performance of the optimally tuned PID controller while outperforming the passive suspension system (Figure 17). The passive suspension exhibited significant oscillations, resulting in poor ride comfort and stability. In contrast, both PID and NN controllers-maintained body displacement within a narrow range, with the NN achieving fluctuations between -0.01 m and 0.01 m, which is substantially better than the passive system. This demonstrates that the NN successfully learned the PID's control strategy and further optimized it to handle nonlinear dynamics effectively. NN's ability to maintain minimal oscillation under periodic disturbances highlights its robustness and adaptability, ensuring improved vibration suppression and enhanced ride comfort compared to conventional methods.

When subjected to random road excitation, the Neural Network (NN)-controlled active suspension demonstrated superior performance compared to both passive suspension and PID-controlled active suspension (Figure 18). The passive system exhibited large and irregular fluctuations, compromising ride comfort and stability. The PID controller improved vibration suppression but still showed noticeable variations under unpredictable road conditions. In contrast, the NN-based controller-maintained body displacement within a narrow range of -0.03 m to 0.03 m, effectively reducing oscillations and ensuring smoother ride quality. This improvement highlights the NN's ability to adapt to nonlinear dynamics and optimize control actions in real time, even under highly variable inputs. The results confirm that NN-based active suspension provides enhanced vibration isolation and better overall vertical dynamic performance compared to traditional control methods.

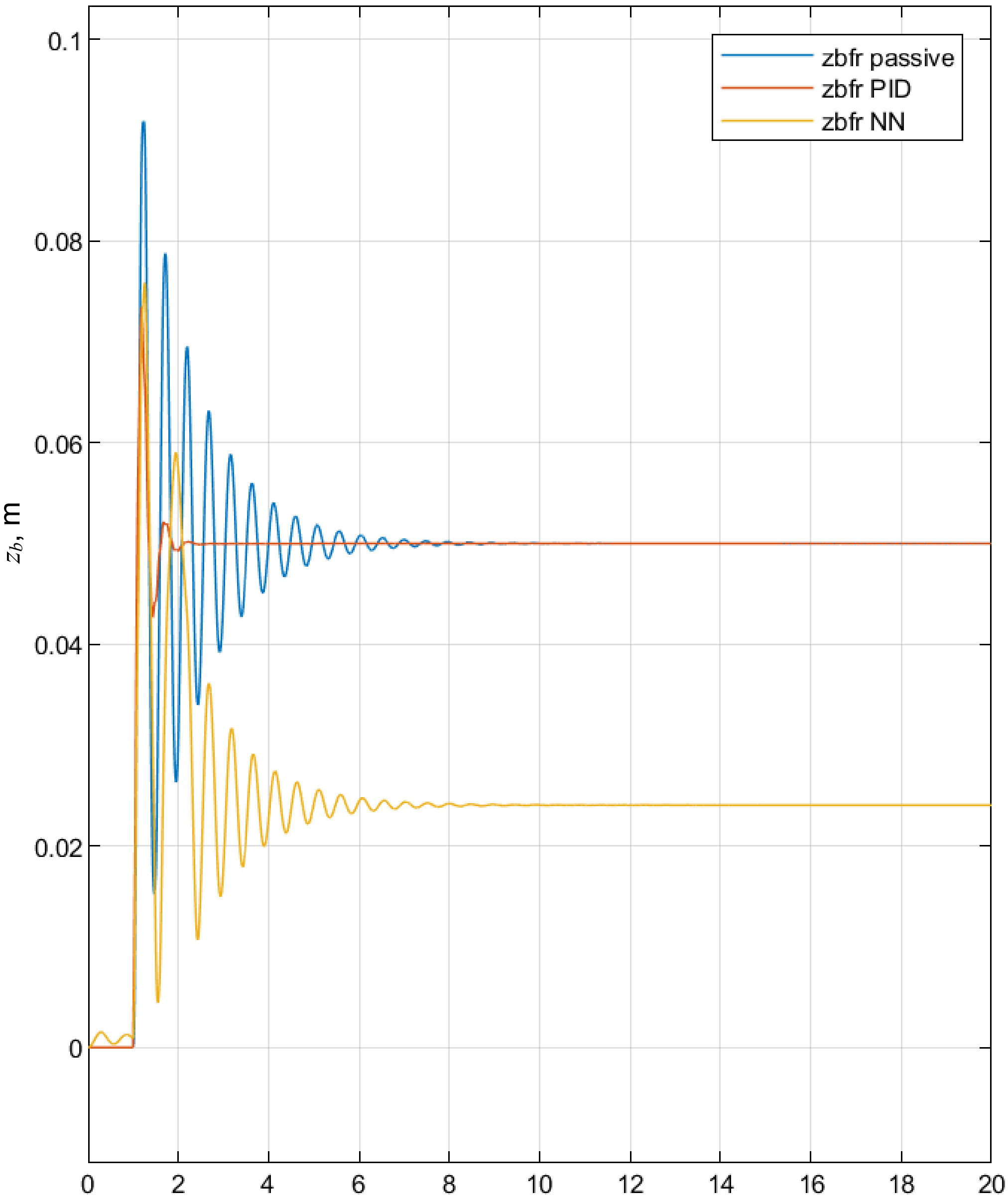

Figure 16. Comparison performance for step input
Source: Author'S work, 2025.

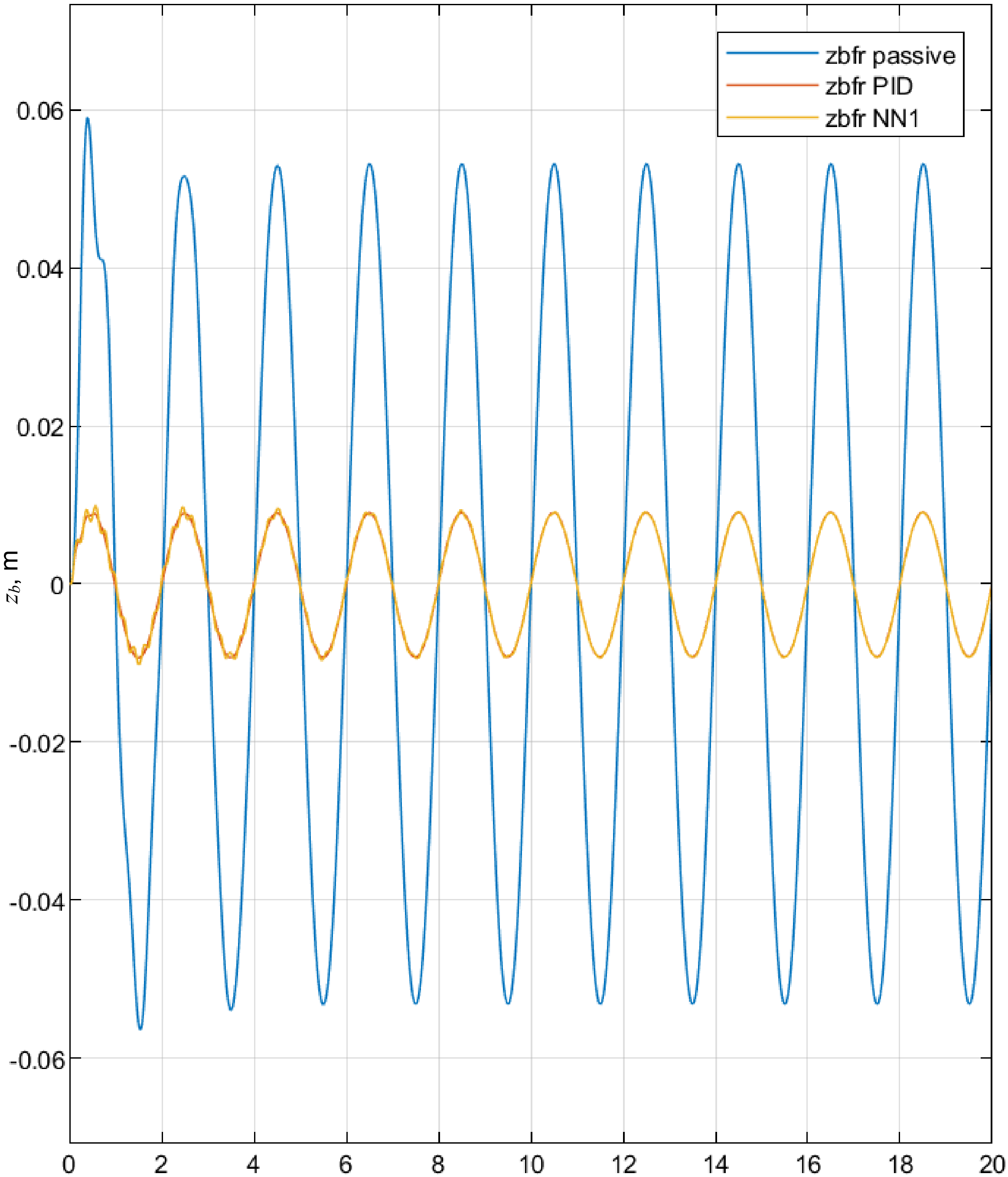

Figure 17. Comparison performance for sine input
Source: Author'S work, 2025.

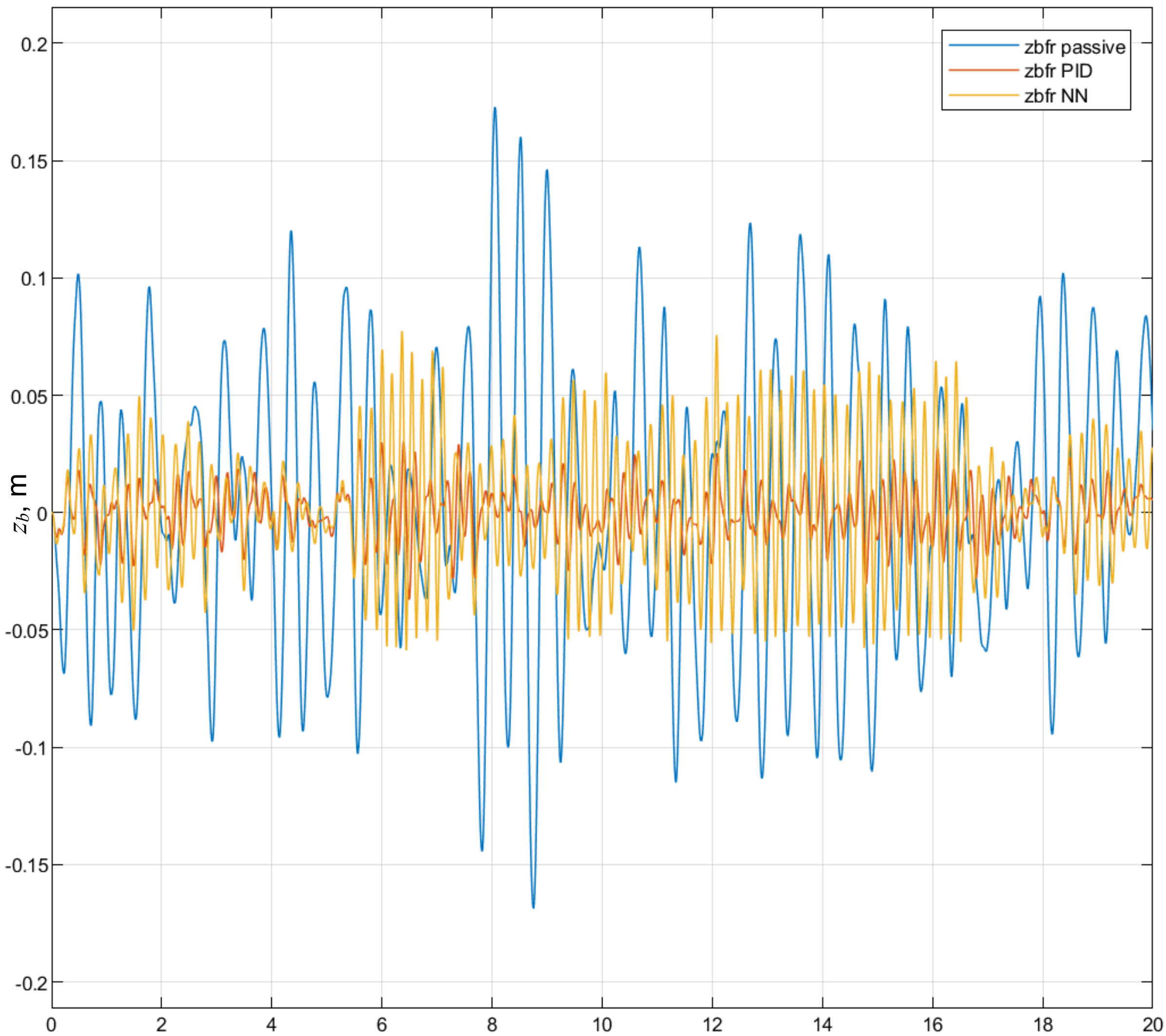

Figure 18. Comparison performance for random input
Source: Author'S work, 2025.

Discussion

The simulation results clearly indicate that active suspension equipped with a PID controller significantly improves vertical dynamic performance compared to a conventional passive suspension system. Passive suspensions rely solely on fixed spring and damper characteristics, which cannot adapt to varying road conditions, resulting in higher body acceleration and greater suspension deflection under disturbances such as bumps or uneven surfaces. In contrast, the PID-controlled active suspension introduces an additional control force that dynamically adjusts based on the error between the desired and actual body position. This adaptive capability enables the system to effectively suppress vibrations and maintain vehicle stability. Performance metrics such as root mean square (RMS) body acceleration and peak displacement demonstrate substantial reductions when using PID control, translating into enhanced ride comfort and improved road holding. Furthermore, the PID controller's derivative action anticipates changes in road input, reducing overshoot and settling time compared to passive systems. Although PID control assumes linearity and may require retuning for different operating conditions, its simplicity and effectiveness make it a practical solution for improving vertical dynamics in active suspension systems.

The integration of a Neural Network (NN) controller that learns from the optimal performance of a PID-controlled active suspension demonstrates a significant advancement in vibration suppression and adaptability. While PID control improves vertical dynamics compared to passive suspension, its fixed gains and linear assumptions limit performance under varying road conditions and nonlinear behaviors. By training the NN on data generated from an optimally tuned PID controller, the NN inherits baseline performance while gaining the ability to approximate complex nonlinear relationships and adapt to dynamic environments. Simulation results show that the NN-based controller achieves lower body acceleration and suspension deflection than PID, particularly under random road profiles and high-frequency disturbances. This improvement is attributed to NN's capability to continuously optimize control actions without manual retuning, ensuring robust performance across diverse operating conditions. Furthermore, the NN reduces overshoot and settling time more effectively than PID, enhancing ride comfort and stability. Although NN implementation requires additional computational resources and training time, its superior adaptability and optimization potential make it a promising solution for next-generation intelligent suspension systems.

Active suspension systems controlled by Neural Networks (NN) outperform PID-based systems primarily due to their ability to handle nonlinearities, adapt to changing conditions, and optimize control actions in real time. PID controllers operate on fixed proportional, integral, and derivative gains, which are tuned for specific operating conditions. This makes PID effective in predictable environments but less robust under varying loads, speeds, and road profiles. In contrast, NN controllers learn complex nonlinear relationships between system states and control forces, enabling them to approximate optimal control strategies beyond the limitations of linear assumptions. By training on data from an optimally tuned PID controller, the NN inherits baseline performance while gaining adaptability to dynamic scenarios such as sudden bumps or random road excitations. Simulation studies consistently show that NN-based control reduces body acceleration, suspension deflection, and tire load more effectively than PID, resulting in improved ride comfort and stability. Additionally, NN controllers exhibit faster response, lower overshoot, and better vibration suppression across a wide frequency range. Although NN requires more computational resources and training time, its superior adaptability and optimization capabilities make it a more advanced and reliable solution for modern active suspension systems.

Conclusion

The study demonstrates that active suspension systems significantly enhance vehicle vertical dynamic performance compared to conventional passive suspensions, with Neural Network (NN)-based control offering the most substantial improvement. While PID-controlled active suspension reduces body acceleration and suspension deflection relative to passive systems, its performance is constrained by fixed gains and linear assumptions, limiting adaptability under varying road conditions. In contrast, NN controllers, trained on optimal PID performance data, leveraged artificial intelligence (AI) to learn complex nonlinear dynamics and optimize control actions in real time. This capability enables superior vibration suppression, improved ride comfort, and enhanced road holding across diverse operating scenarios, including random road profiles and high-frequency disturbances. The application of AI through NN in active suspension systems represents a transformative approach, providing adaptability, robustness, and intelligent optimization that traditional control methods cannot achieve. These findings highlight the potential of AI-driven suspension technologies as a key enabler for next-generation vehicles, particularly in autonomous and electric platforms where comfort and stability are critical design priorities.

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